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The Effect of Innovation on Exports: A Dynamic Panel Approach

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Abstract

Estimation of the effect of innovation on exports raises several specification problems. The mutual causation as predicted by trade and growth theories requires an instrumental variable estimator, which has been accounted for in cross-section analysis. However, the high persistence of exports calls for a dynamic approach. Using an appropriate econometric specification which controls for lagged feedback effects, reverse causation as well as unobserved heterogeneity in a panel of German firms, we find no evidence of a significant causal effect of innovation on exports. This result is robust across alternative specifications and innovation measures.

JEL codes: F1, O3, L1

Keywords: Innovation, export, trade, product cycle, dynamic panel

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1. Introduction

Estimation of the effect of innovation on exports raises several specification problems. First, causation may run both ways: Product cycle models of international trade predict a causal effect of innovation on exports in industrialized countries, whilst global-economy models of endogenous innovation and growth suggest that innovations themselves may be caused by these exports.[1] Hence the potential endogeneity of innovation in an export equation requires an instrumental variables estimator in regression, which has been taken account of in recent cross-section evidence.[2] However, the high persistence of exports calls for a dynamic approach. This will control for lagged feedback effects. Panel data provide a convenient way to do so as they allow for both the cross-section and the time dimension to be exploited in regression. Moreover, even if the coefficient on the lagged dependent variable may not be of interest per se, allowing for dynamics may be important for obtaining consistent estimates of other explanatory variables. In addition, the panel estimator can control for unobserved heterogeneity between the individual cross-section units. The purpose of this paper is to test for the presence of a positive causal effect of innovation on exports in a dynamic panel.

Using a uniquely rich micro dataset of German manufacturing firms over the estimation period 2000-2003, we identify an appropriate econometric specification which controls for lagged feedback effects, reverse causation as well as unobserved heterogeneity. We find no evidence of a significant and positive causal effect of innovation on exports. This result is robust across alternative specifications and innovation measures, including product versus process innovation as well as innovation expenditure.

[1] See, for instance, Vernon (1966) and Krugman (1979) for product cycle models and Grossman and Helpman (1991) as well as Young (1991), e.g., for endogenous growth theories.

[2] See, for example, Lachenmaier and Wößmann (fc.).

The paper is structured as follows. In section 2, we give an overview of the existing literature on innovation and exports, and section 3 describes the dataset and provides some descriptive statistics. The empirical analysis is presented in section 4, where we first identify an appropriate estimator, followed by an application to different measures of innovation and an economic interpretation of the results. Section 5 concludes.

2. The literature on innovation and exports

Theoretical contributions that give support to a causal effect of innovations on exports are mainly Posner (1961), Vernon (1966) and Krugman (1979). Posner postulated the imitation gap theory, which predicts the innovator has a temporary monopoly until foreign firms imitate the new products. Similarly, the product cycle theory (Vernon 1966, Krugman 1979) predicts that industrialized countries need to continuously innovate in order to defend their position on the world market. Otherwise, less industrialized countries, in which labour is cheaper, will eventually imitate their products and increase their shares on the world market.

An extensive body of empirical literature tests the theoretical prediction that innovation affect exports. Greenhalgh (1990) and Greenhalgh et al. (1994), for example analyse the effect of innovation on a sectoral level, showing that sectors with high innovation have higher exports. More recently, the increasing availability of more extensive micro data has allowed for analyses at the firm or plant level. Examples include Wakelin (1998), Sterlacchini (1999, 2001) as well as Bleaney and Wakelin (2002). Wakelin (1998) uses a two-stage model allowing for different effects of innovation on export probability and export propensity, where the number of innovations has a positive effect on the export probability for the sub-sample of innovators. This two-stage strategy is also used later by Basile (2001) for Italian data, showing that the export intensity is higher for innovators than for non-innovators.

Many studies have become increasingly aware of the estimation problems arising from the mutual causation as predicted by trade and growth theories but have been limited by a lack of data on innovation. Early examples include Keesing (1967) or Mansfield et al (1979), while more recent contributions are Bernard and Jensen (1999) and Clerides et al. (1998), for instance. While these studies mainly use identification strategies based on the concept of granger causality, a recent cross-section analysis by Lachenmaier and Wößmann (fc.) uses exogenous innovation impulses and obstacles as instruments for endogenous innovations. This strategy enables them to draw conclusions on the causal effect of innovation on exports, controlling for any potential reverse causation effects.

A recent analysis by Criscuolo et al. (2005) using CIS data for the UK examines the opposite direction of causation and shows that globally engaged firms tend to innovate more. The main underlying reason is not only that these firms employ more researchers but also that they learn from exporting. Evidence of learning from exporting can also be found in earlier studies, e.g. World Bank (1993) as well as Evenson and Westphal (1995). With respect to analyses of potential causal effects of innovation on exports, these findings support the importance of an estimation strategy that controls for reverse causation effects in the innovation coefficient.

The importance of accounting for the persistence of exports has also been addressed in the literature. Roberts and Tybout (1997), for instance, postulate the sunk costs hypothesis using data for Colombian plants. A firm faces high costs when expanding its business to foreign markets. However, post entry these costs are sunk so that the firm is likely to continue exporting. The authors calculate the transition rates between exporting and non-exporting and vice versa and show that switches in the export status are very rare. Bernard and Jensen (2004) and Bernard and Wagner (2001) use dynamic panel estimation to analyse the effect of different firm performance measures on the export status of a firm. Bernard and Jensen (2004) provide first evidence that changes in the product mix – which might be related to product innovation – have positive impact on the probability of exporting. In the following, we will use direct measures of innovation in order to test for the presence of a causal effect of innovation on exports when controlling for the persistence of the latter in a dynamic panel framework.

3. Database and descriptive statistics

3.1 The Ifo Innovation Survey

We use data from the Ifo Innovation survey which provides data on our variables for the years 1997-2003. The survey is conducted annually among German manufacturing firms and answered by an average of 1500 firms per year. The survey started in 1982, but unfortunately the export question was introduced on a regularly basis in 1997, which therefore is the first year of our dataset. The observation unit in this survey is a specific product range, i.e. for firms which produce only one good, the questionnaire is related to the whole firm; in firms which produce more than one good the questionnaire is related to only one specific product range. In the following we will refer to "firm" also for the observations which might represent only one product range. Table A1 in the Annex shows the distribution of respondents with respect to their industry sector (NACE 2digit level) for the year 2003. These numbers are compared with data from the German National Statistical Office to check for representativeness. As one can see there are slight differences, for example in NACE categories 15 (Manufacturing of food) or 28 (Manufacturing of metal products). But the overall picture is that the sectors are represented quite well in the Ifo Innovation Survey, so we would not expect a bias towards more or less innovative industries.

The questionnaire contains several questions about the innovation activities of a firm. The questions relate to the year prior to the actual year to assure that all relevant information are available and firms can answer the questions correctly. The first question we use in our study is simply on whether any innovations were introduced during the preceding year. This is a first measure for the innovative output of a firm. An innovation in this questionnaire is defined as a product introduced to the market or a newly implemented production process, so it also includes innovations with a small innovative step. However, we can give more weight to some innovations compared to others. Firms indicate whether any R&D was necessary for their innovations. This is a first indicator for the importance of an innovation, since those innovations which required R&D are probably more important than others. Another measure for the importance of an innovation is whether any patent application was filed for the innovations introduced. We would only expect this to be the case for very important innovations which are expected to yield high returns and are worth wile the not negligible costs of patenting. For all the innovation variables mentioned above we can also distinguish between product and process innovations.[3]

In addition to these output measures, respondents are also asked for their innovation expenditure, which are a measure for the input in the innovation process. In the Ifo Innovation Survey this expenditure includes the usual R&D expenses, but also costs for patents, licenses, etc. The innovation expenditure is measured relative to the sales of the firm. Again, we have information on whether the expenses were spent on product innovations or process innovations.

[3] For a more detailed comparison of these innovation measures with others, see Lachenmaier and Wößmann (fc).

The dependent variable are firms' exports within the given product range. It is measured as the share of total sales which was generated in foreign markets.

Important control variables are taken from the questionnaire, too. The first one is firm size, measured in number of employees.[4] Other control variables used are the regional location of the firm (German states) and the industry sector of the firm (at NACE 2digit level).

3.3 Descriptive statistics

As mentioned in section 3.1 the export question was introduced in 1997. In our sample we only included those respondents which revealed information about both the firms' exports and their innovation behaviour. Afterwards, we dropped outliers in terms of the growth rate of exports, innovation expenses and employment.[5] Due to our estimation strategy we need at least three consecutive years of a firm in the sample. For the reason of robustness we decided to keep only those firms which have answered at least four consecutive times in the period of 1997 to 2003. Since we use the first three years for instrumenting later observations in our regressions, our estimation period is from 2000 to 2003. These data cleaning steps reduce our sample of firms since 1997 from originally 9014 observation of 3039 different firms to 2349 observations from 454 different firms. The following descriptive statistics refer to our estimation period, i.e. from 2000 to 2003, in which we have 1349 observations from 454 different firms.

[4] Those numbers were cross-checked with data from the Ifo Business Survey, which is conducted monthly. In cases of discrepancies in the numbers of employees between the two surveys or missing data in the Innovation Survey, these numbers were replaced by their counterparts of the Ifo Business Survey as they are expected more reliable due to the monthly information.

[5] For each of these variables we dropped the upper percentile in terms of growth rates.

Table 1 gives an overview of the most relevant variables in our estimation models. We transformed the export variable and the innovation expenses variable into log values.[6] The export variable has a mean of 2.3.[7] But one has to keep in mind that there are many non-exporters in our sample, namely 340 observations or 28% of our sample.

Looking at the innovation variables, 45% of the respondents reported that they introduced an innovation. If we split this variable in product and process innovation (which are not mutually exclusive – respondents can introduce no innovation, either product or process innovations or both types) we see that more product than process innovations were introduced. Looking at the importance of innovations, we find that in 38% of all observations innovations were introduced for which R&D was necessary and only in 20% patent applications were filed in the innovation process. Again we find for both categories higher numbers for product innovations than for process innovations. A special hint should be given to process innovation with patent application. They occur very seldom, only in 1.97% of the observations. This fact has to be taken into account when interpreting the coefficient for this variable in the estimation results. The mean for the innovation expenses is 0.7 expressed again in log values. Our main control variable, firm size, has a mean value of 4.7.[8]

[6] The export variable used is log(1 + export share) and the innovation expenses variable is log(1 + innovation expenses share). With this transformation we account for the expected log-linear effects and avoid the problem of taking logarithms of the value zero for non-exporters or non-innovators.

[7] The mean of the original export share variable is at 25%, the median only at 15%, giving support for the log transformation.

[8] The mean of the original number of employees is at 730, but this statistic is driven by some very large firms, the median is at 98 employees. Again, this gives support for the use of taking logarithms.

To give first descriptive results of our analysis we present t-tests in table 2. We test whether the mean value of exports, our dependent variable, is significantly different between innovators and non-innovators. For the distinction of innovators and non-innovators we use different innovation measures as described above. Table 2 shows that for all innovation variables the difference in the mean of the export value is statistically significant on the 1% level.[9] From this result we would expect in our further analysis that innovation show a significant positive effect on exports.

4. Empirical analysis

4.1. The econometric specification

In this section we introduce our dynamic panel data model of the impact of innovation on exports. We use the following basic autoregressive distributed lag model of exports:

$$\ln(E_{it}) = \alpha_1 \ln(E_{i,t-1}) + \alpha_2 I_{it} + \alpha_3 \ln(S_{it}) + f_i + \varepsilon_{it} \qquad (1),$$

where E_{it} denotes exports as a share of turnover in firm i at time t and S denotes employment as a proxy for firm size. I is our main measure of innovation, which is a dummy variable equal to one if the firm introduced an innovation in year t and zero otherwise. This specification extends the model in Lachenmaier and Wößmann (fc.) by allowing for export dynamics in the underlying data generation process. Equation (1) normalizes the export ratio term by using a logarithmic specification of (1 + export ratio).[10] The use of panel data allows

[9] We only show the distinction in product and process innovation once. The results for this distinction for innovations with R&D and innovations with patents remains very similar and shows the same p-values.

[10] As the dataset includes firms that did not export, using ln (export ratio) was not feasible.

to control for unobserved firm-specific effects f_i to the extent that these are additive and broadly constant over time.

As is typical of microeconomic panel data, our dataset has a large cross-section dimension (firms) and a small time dimension (years). Hence we cannot use estimation methods that rely on the time dimension to become large in order to obtain consistent estimates. Furthermore, our model includes (at least one) explanatory variable which is not strictly exogenous (innovation), without specifying its underlying data generation process. Generalized Method of Moments (GMM) estimators are widely used in this context to obtain consistent estimates. However, GMM estimators may be subject to large finite sample biases in cases where the instruments available are weak,[11], and Blundell and Bond (1998) show that this applies in particular to the first-differences estimators in the case of highly persistent series, i.e. such as the export variable in our model. Efficient estimation can be achieved using the Blundell and Bond (1998) GMM systems approach, where the model is estimated in both levels and first differences.[12] In order to identify an appropriate estimation strategy and avoid potential biases, Bond (2002) suggests to investigate the time series properties of the individual series in order to assess how close they are to a random walk, and to compare the consistent GMM estimators to e.g. OLS levels and within groups estimators, where one can exploit the latter two estimators' likely opposite biases related to coefficients on lagged dependent variables in panels with a short time dimension. The OLS levels estimator of α_1 is likely biased upwards in a model such as (1) as a result of the positive correlation of the lagged dependent variable with the error term, due to the presence of the fixed effects. While

[11] See, for instance, Bound et al (1995), Blundell et al (2000) and Blundell and Bond (1998).

[12] This is important as Blundell and Bond (1998) argue that the finite-sample bias is significantly reduced by exploiting the additional moment conditions implied for the levels equations, so that lagged first differences as well as lagged levels are included as instruments.

the within estimator eliminates the fixed effects from the regression by expressing the variables as deviations from their individual means, and hence eliminates this source of inconsistency, Nickell (1981) shows that the transformed lagged dependent variable and the transformed error term are negatively correlated in panels with a small time dimension. The within groups estimator is likely to be biased downwards. A consistent estimator will in general lie between these two. In the case of highly persistent series the GMM first-differences estimator also is likely biased downward (Blundell and Bond, 1998), if not by as much as the within estimator.

In order to identify an appropriate econometric specification with which to assess the impact of innovation on exports when controlling for the latter's (likely) persistence, we thus follow the route suggested in Bond (2002). As regards GMM estimation, two-step estimators are used throughout the analysis. These tend to be more efficient than the one-step estimators, particularly in the case of the GMM systems approach in large samples, while however the standard errors can be severely downward biased (Arellano and Bond, 1991; Blundell and Bond, 1998). Adjusted standard errors are therefore reported, using the finite-sample correction of the asymptotic variance of the two-step GMM estimator derived by Windmeijer (2005).[13]

Table 3 presents the results of a simple AR(1) model for the dependent variable. The ranking of the different estimators is as one might expect from the above discussion, and the GMM systems estimate still suggests a substantial degree of persistence of the export measure. As the moment conditions are overidentifying restrictions, a difference Sargan test (Arellano and Bond, 1991) can be used to test the validity of the additional moments used in the GMM

[13] All computations are done using Stata 9. The GMM estimators are implemented using Roodman (2005).

systems estimator as compared to the GMM differences estimator. The test result (p-value: 0.068) supports the GMM systems specification at conventional significance levels.

Table 4 presents estimation results for the full model (1) using the different estimators. Again we find the expected ranking of the coefficients. The OLS levels coefficient estimate of the lagged dependent variable appears to be upward biased in the presence of fixed effects, and the within estimate appears to be downward biased (and is insignificantly different from zero). The GMM differences estimator lies between the two and is lower than the GMM systems estimator. The GMM estimators are supported by the diagnostic statistics which test the serial correlation properties as well as by the results of the Hansen test of the overidentifying restrictions. In the estimation of the full model, a differences Sargan test strongly supports the GMM system estimator as compared to the GMM differences estimator (p-value=0.838).

In order to avoid any bias of the innovation coefficient due to reverse causation from contemporaneous exports, innovation is not treated as exogenous. The question in the GMM setting then is whether to treat the variable as predetermined or as endogenous. The innovation variable is treated as predetermined in columns [3] and [4], thus assuming that lagged values $I_{i,t-1}$ and longer lags will be valid instruments in the first-differenced equations. If innovation was endogenous however then $I_{i,t-1}$ would not be exogenous to the error term and invalid for use in the instrument matrix. The validity of the Null hypothesis that the innovation variable is predetermined versus the alternative hypothesis that it is endogenous also can be tested with a difference Sargan test (Arellano and Bond, 1991). The tests exploits the fact that the moment conditions specified under the weaker assumption, in our case endogeneity, are a strict subset of the moment conditions under the stronger assumption, in our case that innovation is predetermined. If we cannot reject the Null, we cannot reject validity of the additional moment conditions. In all our specifications, we could not reject the hypothesis that innovation be treated as predetermined. This conclusion was supported by corresponding Wu-Hausman tests throughout. Respective tests for the employment term indicated that it is exogenous in estimation [Chi-squared(1) p-value=0.567]. Year dummies were highly insignificant individually as well as jointly and were thus not included in the remaining regressions; column [6] reports the results from [4] including a full set of time dummies. Hence our strategy to identify an appropriate estimator suggests use of the GMM systems estimator as reported in column [4]. All of the results are robust to using innovation expenditure as an alternative measure of innovation. In the following section, we will use this preferred model in order to analyse the effect of innovation on exports in a dynamic setting.

4.2. The impact of innovation on exports

Table 4 presents results from using different measures of innovation. For ease of comparison, column [1] reproduces the results from [4], Table 3. When we control for reverse causation effects and unobserved heterogeneity between firms in the dynamic panel setting, innovation is not found to have a significant (and positive) effect on exports. This result was robust to changes in the instrument sets, to including year dummies as well as regional and industry dummies, each being jointly insignificant. The autoregressive coefficient is relatively large, indicating a substantial degree of persistency in export behaviour.

In column [2] we report the results of estimating [1] using innovation expenditure as an alternative measure of innovation. Since output measures (e.g. innovation counts) and input (e.g. expenditure) measures of innovation have been shown to be highly correlated (Acs and Audretsch, 1988; Bound et al, 1984, and Griliches et al, 1991; for instance), one should serve as a good proxy for the other. We would thus expect to see very similar results, as is supported by [2] in Table 4.

In line with the cross-section evidence provided in Lachenmaier and Wößmann (fc.), we do not find important differences between the effects of product and process innovation on exports. However as for the overall innovation dummy neither of the innovation types is found to be significant. This also suggests that the insignificant effect in [1], Table 4, is not driven by either of the two innovation types but that the insignificance is homogeneous across the two. This is different when we do not look at the impact of all innovations introduced in a certain year but only at those innovations the introduction of which required the firm to conduct research and development (columns [4] and [5]). We find the positive impact of product innovations as predicted by trade theory, even though the coefficient is significant only at the 10% level. The negatively significant effect found for the overall measure in [4] is driven by process innovations, overcompensating for the positive effect of product innovation. This might imply that firms which invest in improving production processes do this at the expense of product innovations.

Finally, column [7] in Table 4 reports the results of estimating model [1] including also the outlying firms which were excluded from the regressions so far. These firms essentially have no impact on the results. The overall results thus hold for all firms in our sample.

5. Conclusion

[Conclusion to be added]

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Table 1: Descriptive Statistics of Estimation Sample

	n	Mean	Std. Dev.	Min	Max
Export	1349	2.312	1.676	0	4.615
Employees	1349	4.658	1.563	0	11.513
Innovation	1349	0.454		0	1
Product Innovation	1349	0.397		0	1
Process Innovation	1349	0.301		0	1
Innovation (R&D)	1315	0.378		0	1
Product Innovation (R&D)	1342	0.326		0	1
Process Innovation (R&D)	1318	0.198		0	1
Innovation (Patents)	1315	0.198		0	1
Product Innovation (Patents)	1342	0.192		0	1
Process Innovation (Patents)	1318	0.020		0	1
Innovation expenses	1202	0.706	0.878	0	3.434

Table 2: T-Tests of mean values of exports for innovators and non-innovators

	Innovation			Product Innovation			Process Innovation		
	obs	Mean	s.e.	obs	Mean	s.e.	obs	Mean	s.e.
No	736	1.788	0.06	814	1.837	0.060	943	1.994	0.055
Yes	613	2.940	0.06	535	3.034	0.058	406	3.050	0.067
	p-Value: 0.000			p-Value: 0.000			p-Value: 0.000		

	Innovation (R&D)			Innovation (Patents)		
	obs	Mean	s.e.	obs	Mean	s.e.
No	818	1.821	0.059	1054	2.013	0.052
Yes	497	3.132	0.057	261	3.544	0.058
	p-Value: 0.000			p-Value: 0.000		

Table 3: Simple AR(1) model results for the export variable

	(1) OLS Levels		(2) Within Firms		(3) GMM Difference		(4) GMM System	
Lag Exports	0.990	*(0.004)*	-0.053	*(0.090)*	0.149	*(0.170)*	0.710	*(0.103)*
AR(1)					-2.41		-4.49	
AR(2)					-0.71		0.32	
Hansen (p-value)	-		-		0.137		0.054	
No.of observations	1349		1349		1207		1349	
No.of firms			454		454		454	

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Results for different estimation methods

	(1) OLS Levels		(2) Within Firms		(3) GMM Difference		(4) GMM System		(5) GMM System		(6) GMM System	
Lag Exports	0.935***	*(0.011)*	-0.054	*(0.090)*	0.216*	*(0.128)*	0.558***	*(0.106)*	0.475***	*(0.114)*	0.534***	*(0.117)*
Innovation	0.051	*(0.032)*	-0.043	*(0.050)*	-0.058	*(0.047)*	-0.025	*(0.055)*	-0.191	*(0.183)*	-0.022	*(0.066)*
Size	0.033***	*(0.013)*	0.112	*(0.078)*	0.033	*(0.090)*	0.232***	*(0.058)*	0.295***	*(0.069)*	0.245***	*(0.064)*
Year Dummies	-		-		-		-		-		yes	
Hansen p-value (df)	-		-		0.220 (30)		0.389 (38)		0.342 (34)		0.455 (33)	
Difference Hansen	-		-		-		0.838		0.545		0.145	
AR(1)					-3.082		-4.124		-3.960		-3.619	
AR(2)					-0.532		0.176		0.137		-0.335	
Observations	1349		1349		1207		1349		1349		1349	
No. of firms			454		454		454		454		454	

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Estimation results for different innovation measures

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	Innovation		Innovation Expenditure		Product vs Process Innovation		Innovation (R&D)		Product vs Process Innovation (R&D)		Innovation (Patents)		Innovation including outliers	
Lag Exports	0.558***	*(0.106)*	0.725***	*(0.154)*	0.582***	*(0.103)*	0.445***	*(0.104)*	0.576***	*(0.102)*	0.562***	*(0.108)*	0.532***	*(0.103)*
Innovation	-0.025	*(0.055)*											-0.033	*(0.059)*
Innovation Expenditure			0.021	*(0.049)*										
Product Innovation					0.066	*(0.059)*								
Process Innovation					0.021	*(0.047)*								
Innovation (R&D)							-0.134**	*(0.059)*						
Product Innovation (R&D)									0.089*	*(0.049)*				
Process Innovation (R&D)									-0.125**	*(0.049)*				
Innovation (Patents)									-		0.102	*(0.066)*	-	
Size	0.232***	*(0.058)*	0.154*	*(0.079)*	0.211***	*(0.059)*	0.303***	*(0.059)*	0.227***	*(0.058)*	0.224***	*(0.063)*	0.238***	*(0.057)*
Hansen p-value (df)	0.389 (38)		0.606 (38)		0.121 (59)		0.625 (38)		0.770 (59)		0.369 (38)		0.115 (38)	
AR(1)	-4.124		-3.493		-4.194		-3.928		-4.247		-4.107		-4.682	
AR(2)	0.176		-0.407		0.171		0.096		0.173		0.187		0.275	
Observations	1349		1202		1349		1315		1315		1315		1442	
No. of firms	454		428		454		449		449		449		482	

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A1: Representativeness of the Ifo Innovation Survey

	NACE classifictaion	Ifo Innovation Survey		Statistical Office	
15	Food + beverages	81	6.42%	5494	12.41%
16	Tobacco	4	0.32%	32	0.07%
17	Textiles	49	3.89%	1031	2.33%
18	Wearing apparel	29	2.30%	477	1.08%
19	Tanning and dressing of leather	18	1.43%	214	0.48%
20	Wood and of products of wood	55	4.36%	1166	2.63%
21	Pulp, paper + paper products	64	5.08%	998	2.25%
22	Publishing + printing	66	5.23%	2858	6.46%
23	Coke, ref. petrol. prod. + nuclear fuel	4	0.32%	70	0.16%
24	Chemicals + chemical products	101	8.01%	1845	4.17%
25	Rubber + plastic products	72	5.71%	3104	7.01%
26	Other non-metallic mineral products	95	7.53%	2998	6.77%
27	Basic metals	22	1.74%	1078	2.43%
28	Fabricated metal products	113	8.96%	6737	15.22%
29	Machinery + equipment	230	18.24%	7044	15.91%
30	Office machinery + computers	4	0.32%	197	0.44%
31	Electrical machinery + apparatus	86	6.82%	2461	5.56%
32	Radio, TV + communication equipment	24	1.90%	747	1.69%
33	Medical + precision instrum., watches	55	4.36%	2269	5.12%
34	Motor vehicles, trailers and semi-trailers	25	1.98%	1256	2.84%
35	Other transport equipment	7	0.56%	425	0.96%
36	Furniture; manufacturing n.e.c.	57	4.52%	1774	4.01%
		1261		44275	